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Proof of concept of the efficient design method for high-temperature superconducting magnets employing machine learning regression

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Abstract

We present a newly developed machine learning based optimized design method for high-temperature superconducting (HTS) magnet. Previous optimization design methods required performing thousands to tens of thousands of magnet characteristic calculations repeatedly to evaluate the objective functions and constraints. If the computation time for analyzing magnet characteristics was long, the design process inevitably became very time-consuming. In this research, we introduce a method that uses machine learning regression techniques to achieve similar design performance while significantly reducing computation time. XGBoost algorithm was trained to create a virtual model capable of predicting the actual characteristics of the magnet. By utilizing this predictive model, which allows for much faster calculations, rather than directly computing the characteristics during the optimization process, the design process was significantly enhanced in terms of efficiency. The proposed design method was applied to the design of a 2 T-class HTS magnet, and it was confirmed that similar results to the previous design could be achieved much more quickly.

Keywords: HTS magnet, machine learning regression technique, optimized design

1. INTRODUCTION

High-temperature superconductors (HTS), owing to their high critical current capacity and ability to operate without liquid helium, are increasingly being applied in various electrical applications, such as high-field direct current magnets, superconducting synchronous motors, and particle accelerators [1]. Although HTS can achieve performance levels unattainable by other conductors, the high cost of the HTS wire can increase the overall system cost. Therefore, it is essential to optimize the design of HTS-based electrical systems to meet the required specifications while minimizing the use of HTS wire. Various optimization-based design studies for HTS magnets, including those utilizing genetic algorithms (GA) [2-4], have been conducted, and many direct current magnet systems based on such designs are operating successfully [5-7]. However, in cases such as ultra-high magnetic field magnets, where the large number of coil modules greatly increases the computation time for critical current calculation during the design phase, or when the design incorporates three-dimensional structures or nonlinear elements like iron cores, which necessitate finite element analysis (FEM), the application of optimization techniques requiring thousands or even tens of thousands of iterations can be particularly challenging.

In the design of HTS magnet systems, it is expected that time for design process can be significantly reduced by employing regression-based machine learning techniques.

By replacing computationally expensive magnetic and mechanical analyses with trained virtual prediction models that yield nearly equivalent results but require significantly less computation time, the overall efficiency of the design process can be greatly improved [8-11]. In this paper, we propose an optimized design method for HTS magnets based on regression machine learning models. To develop a performance prediction model for HTS magnets, a virtual prediction machine learning model is created by acquiring a training dataset that requires far fewer analyses than would be needed in a purely optimization-based design process. The purpose of this study is to shorten the optimization time by replacing the time-consuming analysis steps with the prediction machine learning model during the actual optimization process, while still achieving results comparable to those of conventional design methods. To verify the feasibility of the proposed design method, a 2 T-class HTS magnet composed of multiple double-pancake coils (DPC) was designed employing the regression machine learning model, and the results demonstrate the performance of the proposed method.

2. OPTIMIZED DESIGN PROCESS EMPLOYING REGRESSION-BASED MACHINE LEARNING

2.1. The main structure of the overall algorithm

The overall design process is divided into two main step: (1) training a magnet performance prediction model using actual analysis data, and (2) conducting optimization design based on the trained prediction model. Fig. 1 shows

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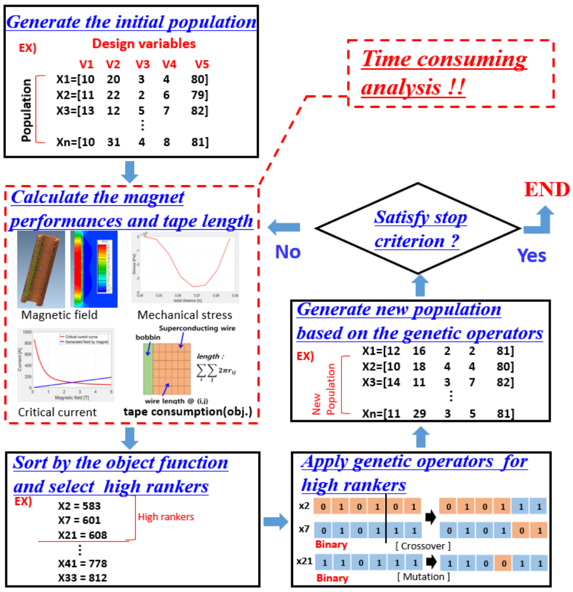
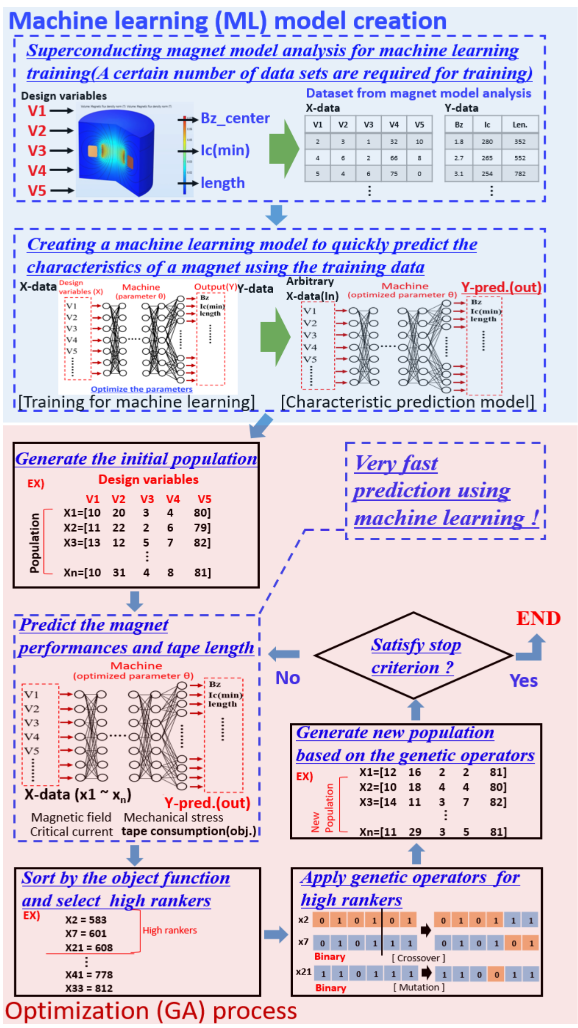
the difference between previous optimization process and the proposed machine learning based process.



(a)



(b)

Fig. 1. Magnet design process of the (a) previous optimization method and the (b) proposed method.

As represented in Fig. 1, previous optimization methods [2,3] involve directly calculating the magnet characteristics to calculate the objective function and determine any constraint violations. If this calculation is time-intensive, it can substantially extend the overall design process. In contrast, the method proposed in this study replaces the evaluation of the objective function and the determination of constraint violations, which were previously performed through direct analysis of the magnet, with a pre-trained regression-based virtual prediction model. This substitution allows for obtaining comparable results while significantly reducing computation time. Of course, to create a magnet performance prediction model, a training dataset consisting of HTS magnet performance data under various design conditions is essential. To obtain this data, a certain amount (significantly fewer than the number of analyses performed in conventional optimization methods) of actual magnet analysis must be repeatedly implemented. That is, for arbitrary design variables, characteristics such as the central magnetic field and critical current of the magnet must be obtained using analytical techniques or finite element methods, and these values must be compiled into a dataset. The dataset is composed of X-data, representing the design variables, and Y-data, which corresponds to the magnet's characteristics associated with those design variables. By training a machine learning model using the X and Y data, a model can be obtained that quickly computes the magnet's performance, represented by Y, through regression theory, without the need for actual magnet analysis when an arbitrary X value is input [8-11]. After the machine learning model for predicting the characteristics of the magnet is developed, the optimization design process remains the same as previous methods, except that the calculations of magnet characteristics are carried out using the machine learning regression model rather than direct analysis.

2.2. Magnet performances prediction model using eXtreme Gradient Boosting (XGBoost) algorithm

We have chosen XGBoost as the machine learning model to predict the continuous values of the magnet's characteristics based on various design variables. XGBoost is a decision-tree-based ensemble machine learning algorithm that uses boosting to improve predictive accuracy. It operates by sequentially building a set of weak learners, typically decision trees, where each new tree corrects errors made by the previous ones. XGBoost optimizes a custom loss function through gradient descent, adding trees until no further significant improvement is achieved [8-11]. While deep learning-based regression models are also viable, XGBoost is more suitable for achieving the goals of the proposed method. This is because the optimal amount of training data for this task ranges between 1,000 and 2,000, and for such a relatively small dataset, XGBoost tends to provide better prediction accuracy compared to deep learning models.

3. DESIGN OF A 2-TESLA CLASS HTS MAGNET EMPLOYING THE PROPOSED METHOD

3.1. Design Specifications of the 2 T class HTS magnet

The HTS wire used in the design is SuNAM ReBCO tape, with a thickness of 0.14 mm and available in two widths: 4.1 mm and 6.1 mm. To protect the magnet, a 50 µm thick Stainless steel tape is co-wound together, resulting in a total thickness of approximately 0.19 mm per turn. And it is assumed that the HTS magnet composed of DPCs operates at 20 K using a conduction cooling method. The objective function of the 2 T-class HTS magnet is the consumed HTS wire length and the two nonlinear constraints are: 1) center magnetic field > 2 T and, 2) the operating current value should be less than 70% of the minimum critical current of the magnet when the operating current is applied. There are five design variables related with the magnet specifications. The Fig. 2 shows the design variables, objective function and nonlinear constraints of the HTS magnet.

3.2. Magnet characteristics prediction model training

Approximately 2,000 unique design variable combinations (X-data), evenly distributed across the design variable range, were generated. Using the actual magnet model, the central magnetic field, minimum critical current current, and total wire length (Y-data) corresponding to each set of design variables were calculated to prepare the training data. The prediction model was trained using the 2,000 data-sets in google Colab environment. The XGBoost library with the GridSearchCV library for hyper-parameter tuning was applied to train the magnet characteristics prediction model. Model training was carried out using 1,760 data points, which account for approximately 88% of the total data, while the remaining data was reserved for validation after the model was created.

After completing the model training, the performance of the predictive model was evaluated using the reserved validation data (240 data) to confirm how accurately it predicted the magnet characteristics. As a result, an average difference of approximately 0.008 T in the central magnetic field and around 0.126 A in the critical current was observed. The detailed differences between the actual calculated values and the predicted for 240 validation data points are shown in Fig. 3. Since the two values are nearly identical, it is possible to evaluate the characteristics of the magnet using predictions from this virtual model without performing actual magnet analysis in the optimization process. The small differences in the Fig. 3 are influenced by factors such as the amount of data used for training and the hyper-parameters of the machine learning model.

3.3. Optimization process with the prediction model

The optimized magnet design process using the prediction model was also implemented in the Google Colab environment, utilizing the PyGAD library for GA optimization. The number of generations for the GA was set to 100, and the population size to 60. The part that calculates the characteristics of the magnet was replaced with the proposed prediction model for optimization, and the design results are represented in TABLE I.

The specifications of the computer used for computation are as follows: 1) CPU: Intel I9-11900K @ 3.50GHz, and 2) GPU: NVIDIA GeForce RTX 3080.

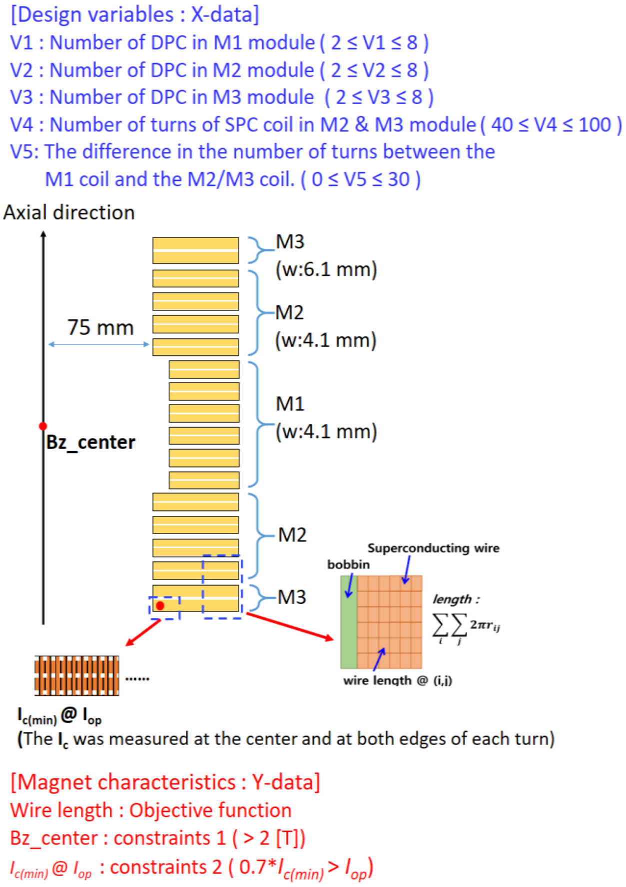


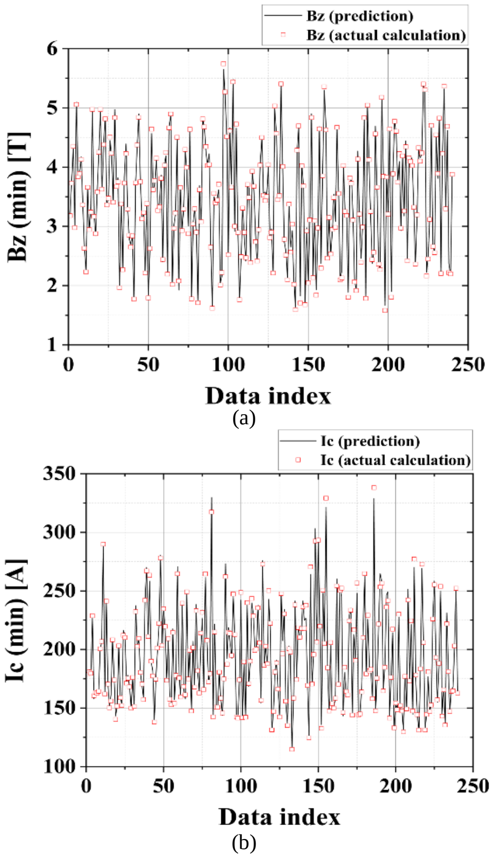
Fig. 2. The five design variables (X-data), objective function and constraints (Y-data) of the HTS magnet.

TABLE I
SPECIFICATIONS OF THE DESIGNED 2 T HTS MAGNET WITH THE PROPOSED METHOD.

Parameters	Value
Design variables	[2, 5, 3, 42, 0]
Center field	2.0 [T]
$I_{c(min)}$ @ I_{op}	350.3 [A]
Wire consumption	< 871.4 [m]
Computation time	< 3000 [s]

The design results obtained using the proposed method were analyzed with COMSOL to validate the performance of the design approach as shown in Fig 4. It can be confirmed that the calculated center field and minimum critical current values at the operating current from the COMSOL results are similar to the results from the magnet characteristics prediction model applied in the proposed design method (TABLE I).

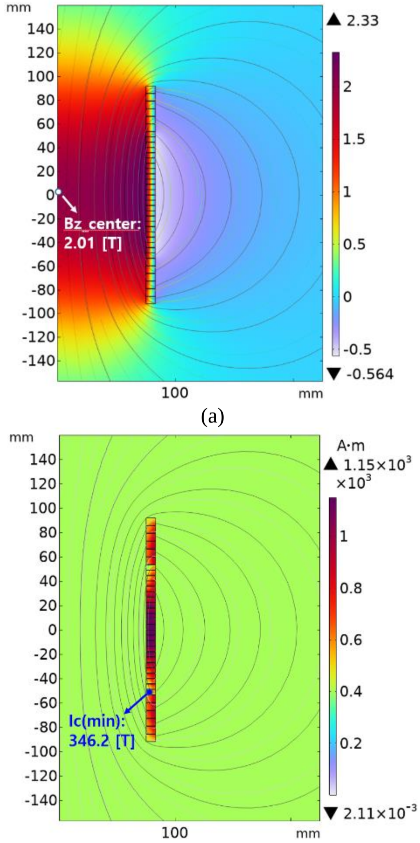
Note that the entire process was completed in under 3,000 seconds, with approximately 2,000 seconds spent on collecting training data, 900 seconds on training and tuning the machine learning model, and around 10 seconds for the actual optimization process using the prediction model. The reason the design process was able to proceed so quickly is that, during the optimization, the magnet's characteristics were not analyzed directly. Instead, a prediction model, which takes less than a millisecond, was used. When calculating the magnet's characteristics



(a)

(b)

Fig. 3. Comparison graphs between the actual calculated results and the prediction results of (a) the center field and (b) the minimum critical current, obtaining from the 240 validation data.



(a)

(b)

Fig. 4. Finite element method (COMSOL) results of the 2 T HTS magnet designed from the proposed design method: (a) center field, (b) minimum critical current.

analytically, the magnetic field values must be computed at three points for each HTS turn (the center and both ends), converted into the field's strength and angle, and then applied to the interpolation formula (SuNAM Ic data @ 20 K) for various wire angles and amplitudes to determine the critical current. This process is very time-consuming, and for a 2 T-class model, it typically takes more than one second per an analysis. If optimization is performed under the same conditions using the method of directly calculating the magnetic field characteristics, the computation time is expected to exceed 6,000 seconds arithmetically.

For a practical comparison with previous design methods, the same design was carried out in a MATLAB environment with the conventional GA library where the characteristics of the magnet could be directly calculated. Through the comparative design process, results were obtained after approximately 10,000 seconds, with a central magnetic field of 2.01 T, a minimum critical current of 345.5 A, and a total wire consumption of 865.7 m. Although the two design results were nearly identical, it was observed that the computation time of the proposed method was about only 30% of that of the previous method. Furthermore, if the magnet's characteristics are analyzed using finite element method, each analysis can take tens of seconds to several minutes, and in such cases, the whole optimal design process could take several days.

4. CONCLUSION

This paper presents an optimized design method for HTS magnets based on machine learning regression techniques. The proposed design method has the advantage of significantly reducing computation time by replacing the time-consuming analysis of HTS magnet characteristics with a pre-trained regression model, allowing for similar results during optimization while drastically cutting down the computation time. To validate the performance of the proposed method, it was applied to predict the magnet characteristics of a 2 T HTS magnet operating at 20 K. After training the XGBoost regression model with 1,760 training data, its predictive performance was evaluated using 240 validation data. The results demonstrated very small errors, with an average deviation of about 0.008 T for the central magnetic field and 0.126 A for the minimum critical current. These results demonstrate that, during the optimization process, it is possible to quickly predict the magnet characteristics using a regression model, without the need to perform the time-consuming calculations directly. The proposed regression model was applied to a GA for optimal design, resulting in the design of a 2 T magnet with a 150 mm bore using approximately 870 meters of HTS wire based on a 4.1 mm standard. The computation time was less than half of what would have been required without this method. Furthermore, if this approach were applied to models that include nonlinear elements such as iron cores or require 3D finite element method, the reduction in computation time is expected to be significantly greater.

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REFERENCES

[1] "National High Magnetic Field Laboratory," Accessed: Oct. 1, 2024, [online]. Available: https://nationalmaglab.org/magnet-development/applied-superconductivity-center/plots.

[2] J. Y. Jang, et al., "Design and Quench Protection Analysis of a 9 T NbTi Superconducting Magnet for a Large-Bore EMPS," *IEEE Trans. Appl. Supercond.*, vol. 30, no. 4, pp. 9500205, 2020.

[3] J. Y. Jang, et al., "Development of a Cryogen-Free Compact 3 T Superconducting Magnet for an Electromagnetic Property Measurement System," *Appl. Sci.*, vol. 11, no. 7, pp. 3071, 2021.

[4] S. Nam, et al., "Optimized Design of a 170-GHz Gyrotron Magnet With Thermally Insulated Structures," *IEEE. Trans. Appl. Supercond.*, vol. 32, no. 6, pp. 3700505, 2022.

[5] K. L. Kim, et al., "400-MHz/60-mm All-REBCO Nuclear Magnetic Resonance Magnet: Magnet Design," *IEEE. Trans. Appl. Supercond.*, vol. 26, no. 4, pp. 4302604, 2016.

[6] K. Kim, et al., "Design and performance estimation of a 35 T 40 mm no-insulation all-REBCO user magnet," *Supercond. Sci. Technol.*, vol. 30, pp. 065008, 2017.

[7] K. Kim, et al., "Design and Performance Estimation of a 20 T 46 mm No-Insulation All-REBCO User Magnet," *IEEE. Trans. Appl. Supercond.*, vol. 30, no. 4, pp. 4602205, 2020.

[8] "XGBoost Python Package," Accessed: Oct. 1, 2024, [online]. Available: https://xgboost.readthedocs.io/en/stable/python/

[9] T. Chen and C. Guestrin, "XGBoost: a scalable tree boosting system," *In Proc. 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 785-794, 2016.

[10] "Machine learning models for predicting the residual value of heavy construction equipment: An evaluation of modified decision tree, LightGBM, and XGBoost regression," 2022.

[11] "An XGBoost-based physical fitness evaluation model using advanced feature selection and Bayesian hyper-parameter optimization for wearable running monitoring," 2019.